MRI Tissue Segmentation: Comparative Analysis of 2D and 3D Approaches

Module: Computer Vision and Imaging Extended [06 30241]
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Introduction

This study aims to test and evaluate 2D and 3D segmentation algorithms for segmenting MRI brain slices into distinct tissue layers. We implemented Otsu’s thresholding, multi-Otsu thresholding, K-Means clustering, and edge detection techniques. The segmented results are evaluated against ground-truth labels to determine the most accurate approach for solving this task.

Data and Preprocessing

- **Dataset**: 10 axial MRI slices, each 362x434 pixels, with six different class labels: air, skin/scalp, skull, CSF, grey matter, and white matter.

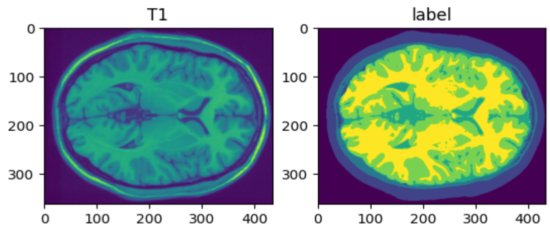

Figure 1: Slice of MRI Image Data

- **Preprocessing**: Gaussian smoothing (sigma(σ)=1) was applied to reduce noise and standardise intensity values. This step helps reduce random intensity fluctuations and enhances tissue boundaries, making it easier to segment difficult-to-differentiate classes within the image.

2D Segmentation Algorithms

Multiple segmentation techniques were applied to the MRI data to identify and differentiate five distinct tissue layers. These methods included **Otsu's thresholding**, **filtering techniques** (Canny and Sobel edge detection), **K-Means clustering**, and **multi-Otsu thresholding**.

Multi-Otsu Thresholding extends Otsu's thresholding for multi-class segmentation, dividing the intensity range into **k** intervals that minimise intra-class variance. In 3D, the method processes the entire volume, determining thresholds that apply across all slices. Multi-Otsu iterates through possible threshold combinations to find those that minimise the weighted sum of intra-class variances:

$$\boldsymbol{\sigma_w^2 = \sum_{\{i=1\}}^{\{k\}} \omega_i \sigma_i^2} \text{-}$$

where $\omega_i$represents the probability (weight) of class i, and σ_i^2 is the variance within class i.

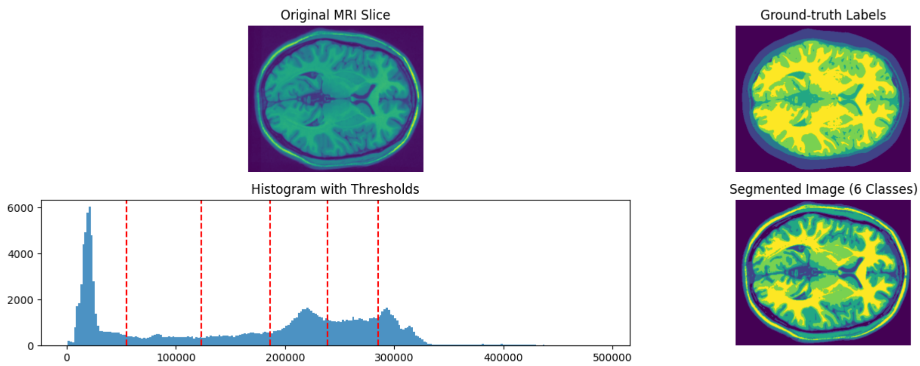

Figure 2: Multi-Otsu Thresholding Algorithm

Evaluation of 2D Segmentation Algorithms

Otsu's thresholding was utilised for binary segmentation by determining an optimal threshold to separate the foreground and background. Filtering techniques, specifically Sobel and Canny edge detection, aimed to highlight tissue boundaries by detecting intensity gradients. However, these methods struggled with noise and produced low accurate results due to the complex structure and multiple labels of MRI images.

K-Means clustering effectively handled intensity variations but was sensitive to initial centroid positions, requiring careful preprocessing. Multi-Otsu thresholding, an extension of Otsu's method, provided a robust approach for multi-class segmentation by partitioning the intensity histogram into multiple classes, offering better performance for differentiating complex tissue types, at the cost of extensive computation.

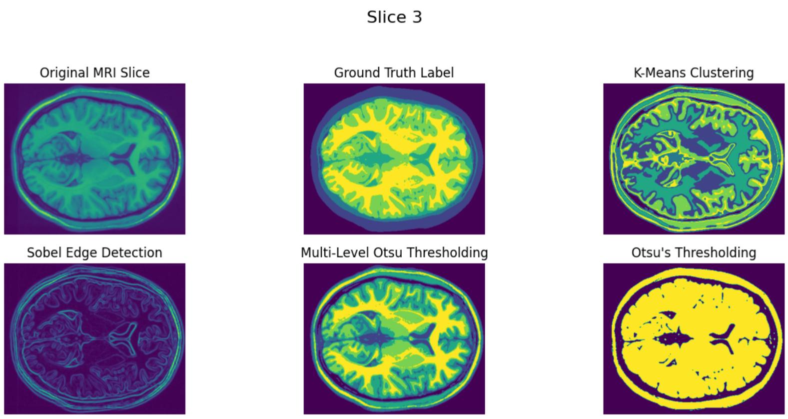

Figure 3: Comparison of 2D Segmentation Algorithms

Metrics for Image Segmentation

The evaluation of the various segmentation algorithms in this study was conducted using the following metrics:

- **Dice Coefficient:** Measures the overlap between the segmented result (A) and the ground-truth labels (B). It ranges from 0 to 1, where 1 indicates perfect overlap.
- **Intersection over Union (IoU):** Quantifies the ratio of the intersection and union of the segmented output (A) and ground truth (B). Values close to 1 indicate high segmentation accuracy, meaning a large portion of the segmented and ground-truth regions overlap.
- **Accuracy:** Represents the percentage of correctly classified pixels in the segmented image compared to the ground-truth labels.
- **Normalized Surface Distance (NSD):**
  Evaluates the alignment accuracy of boundaries between the segmented output and the ground-truth labels. Higher NSD values indicate better alignment of segmentation boundaries with the ground truth.

All ten slices of the MRI images were segmented and evaluated for each method, with the results analysed separately for each class. The average performance metrics across all slices are summarised in the table below.

Table 1: Evaluation Table for 2D Segmentation Algorithms

Method	Dice Coefficient	IoU Score	Accuracy	NSD
K-Means	0.547	0.468	0.882	0.345
Sobel	0.071	0.045	0.757	0.000
Otsu	0.230	0.178	0.839	0.079
Multi-Otsu	0.584	0.511	0.918	0.405

The evaluation metrics provide insights into the performance of each segmentation method. **Multi-Otsu** demonstrated the highest performance, with a Dice Coefficient of 0.584 and an IOU score of 0.511, indicating strong overlap with the ground-truth labels. Its accuracy of 91.8% and NSD of 0.405 highlight its ability to align well with true tissue boundaries, effectively handling the complexity of multiple tissue classes. **K-Means** showed moderate performance (Dice: 0.547, IOU: 0.468), suggesting effective segmentation but slightly lower boundary alignment (NSD: 0.345). In contrast, **Otsu's thresholding** (NSD: 0.079) and **Sobel edge detection** (NSD: 0.000) exhibited poor boundary alignment, indicating their inability to handle the segmentation of multiple classes in complex MRI images. These results suggest that multi-Otsu is the most effective method for this project, offering robust and accurate segmentation of MRI slices.

3D Segmentation Algorithms

Two 3D image segmentation techniques, **3D K-Means clustering** and **3D multi-Otsu thresholding** were applied to segment the MRI slices simultaneously, treating the entire volume as a cohesive dataset. In these methods, the 3D volume was flattened into a single array, and segmentation was performed in one operation, ensuring spatial consistency across slices. In the 3D version, the entire MRI volume is treated as a single dataset, and each voxel is assigned to one of the **k** clusters based on its intensity value.

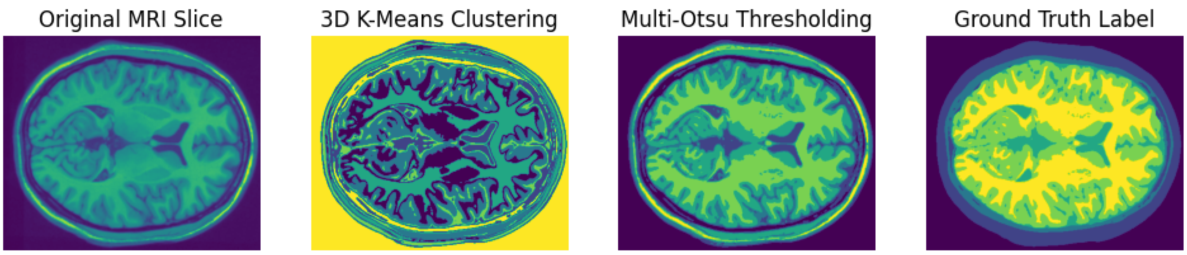

Figure 4: Comparison of 3D Segmentation Algorithms

Evaluation of 3D Segmentation Algorithms

The comparative analysis of 3D segmentation methods highlights notable distinctions in performance and computational efficiency. The 3D multi-Otsu thresholding algorithm demonstrated superior segmentation accuracy, with robust boundary alignment and strong concordance with ground-truth labels. This method effectively captured the complex structures within MRI volumes, underscoring its suitability for applications where precise tissue differentiation is critical. Although its runtime is longer compared to 3D K-Means, it remains substantially more efficient than the 2D equivalent, offering a balanced approach between computational cost and segmentation accuracy.

In contrast, 3D K-Means exhibited the shortest runtime while maintaining competitive performance metrics. Its ability to produce accurate segmentations with significantly reduced computational overhead makes it a compelling choice for time-sensitive or resource-constrained applications. The method's efficiency in processing volumetric data underscores its potential for integration into real-time clinical workflows or large-scale data processing tasks.

Table 2: Evaluation Table for 3D Segmentation Algorithms

Method	Dice Coefficient	IoU Score	Accuracy	NSD	Runtime (sec)
3D multi-Otsu	0.587	0.485	0.919	0.395	101.060
3D K-Means	0.566	0.514	0.908	0.439	0.410
K-Means	0.547	0.468	0.882	0.345	0.444
Multi-Otsu	0.584	0.511	0.918	0.405	997.049

Conclusion

This study compares 2D and 3D segmentation methods for MRI tissue analysis. 3D multi-Otsu exhibited strong accuracy and boundary alignment, making it suitable for precision-focused applications. In contrast, 3D K-Means provided competitive performance with significantly reduced runtime, making it effective for time-sensitive tasks. The choice of method depends on balancing accuracy and computational efficiency, with 3D approaches demonstrating better spatial coherence across slices.